A Blended Satellite–In Situ Near-Global Surface Temperature Dataset
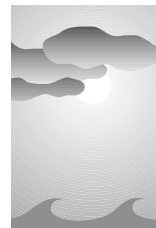
Thomas C. Peterson,* Alan N. Basist,* Claude N. Williams,* and Norman C. Grody+

ABSTRACT

A near-global surface temperature dataset was produced by blending several sources of information. For the oceans, these include in situ and infrared satellite-derived sea surface temperatures that were already processed into a monthly product. Land data analysis uses two sources of data. The first is high quality monthly in situ reports from the Global Historical Climatologic Network with more than 1000 stations from around the world. The second source of information is the recently developed passive microwave satellite-derived land surface temperature derivation methodology described in Williams et al. These data are blended on a $1° \times 1°$ grid that excludes only ice- and snow-covered regions lacking in situ observations. Available starting in January 1992 and updated 10 days after the end of the calendar month, this product is useful for monitoring regional climate anomalies and provides insights into climate variations.

1. Introduction

Our quest was to produce a gridded global surface temperature dataset with an accuracy and a spatial resolution fine enough to clearly identify and delineate regions with significant monthly scale climate anomalies. Due to the limited observations and international exchange of high quality in situ data, satellite-derived surface temperature data would be required. Reynolds and Smith (1994) already produce a satellite–in situ blended sea surface temperature dataset of the quality and resolution required. But until recently, no high quality satellite-derived land surface temperature dataset was available to blend with in situ observations.

Deriving monthly scale land surface air temperatures poses significant problems for researchers. Land temperatures are far more variable, both in time of day and from day to day, than sea surface temperatures (SST). The inability of infrared emissions from the

*National Climatic Data Center/NESDIS/NOAA, Asheville, North Carolina.
+Office of Research and Applications/NESDIS/NOAA, Camp Springs, Maryland.
Corresponding author address: Thomas C. Peterson, National Climatic Data Center, 151 Patton Avenue, Asheville, NC 28801.
E-mail: Thomas.C.Peterson@noaa.gov
In final form 25 February 2000

surface to reach a satellite during cloudy conditions biases infrared temperature retrievals to cloud-free times. Therefore, the authors developed a methodology to derive surface temperatures from passive microwave emissions that are not biased by most cloud conditions (Basist et al. 1998; Williams et al. 2000). This method makes pixel by pixel assessments of the surface emissivity and adjusts the observed brightness temperature accordingly. While the accuracy and spatial resolution were high enough for use in this global product, this approach cannot derive surface temperatures over most snow and ice surfaces.

However, providing full land coverage in the in situ data-sparse Tropics is very valuable. For land surface temperatures, these satellite-derived analyses were blended with and anchored to in situ mean monthly temperature observations. Then the land and ocean observations were merged to produce near-global coverage. The spatial resolution of the dataset was defined by the existing $1° \times 1°$ SST database. The Special Sensor Microwave/Imager (SSM/I) data could provide $1/3°$ resolution but averaging up to the SST's $1° \times 1°$ made the dataset more robust by helping remove outliers (the averaging being done with a biweight approach; Lanzante 1996). The temporal resolution, monthly, was defined by high quality internationally exchanged in situ climate reports that are more reliable than calculating, for example, weekly means from incomplete synoptic reports. And the period of record

was governed by data availability from the passive microwave satellite instrument used. The data start in January 1992 and are updated about 10 days after the end of a month.

The exact definition of *surface* in this surface temperature product varies with the data source. Sea surface temperatures, for example, come from a blend of near-surface in situ observations and IR skin temperature observations. In situ land observations are point measurements of near-surface air temperature, usually taken ~1.5 m above the ground. And the microwave emissions observed by the SSM/I originate primarily from the earth's surface in bare ground conditions but from the canopy in vegetated environments. Because each of these data have different biases relative to a "true" surface temperature, the final product only uses anomalies from each data source. Using only monthly anomalies removes the major biases not only to the true surface temperature but also biases to the time of day the observations were made (Williams et al. 2000).

2. Sea surface temperature data

The source of sea surface temperature data is the well-known National Oceanic and Atmospheric Administration (NOAA) operational 1° latitude by 1° longitude gridded dataset (Reynolds and Smith 1994; Reynolds and Marsico 1993). The source data include ship and buoy in situ data as well as satellite-derived SSTs. The satellite observations are from the infrared window channels on the Advanced Very High Resolution Radiometer (AVHRR) that is flying on the NOAA polar-orbiting satellites. These data are produced operationally by NOAA's Environmental Satellite, Data, and Information Service (NESDIS). The satellite SST retrieval algorithms are "tuned" by regression against quality controlled drifting buoy data.

Quality control procedures include tracking tests to remove ship or buoy observations with unlikely positions. All observations, both in situ and satellite, are discarded if the SST value is less than −2°C or greater than 35°C or if the SST anomaly lies outside the ±3.5 times the climatological standard deviation. These tests remove the worst data. Biases in satellite-derived SSTs relative to in situ data, such as those caused by volcanic eruptions, are adjusted for using a spatial smoothing technique. The final SST product is based on optimum interpolation (OI) at a 1° grid.

3. In situ land surface air temperature data

The source of in situ temperature data from land stations is the Global Historical Climatology Network (GHCN; Peterson and Vose 1997). GHCN is a century-scale dataset with more than 7000 stations reporting mean monthly temperature derived from daily or more frequent weather observations. While several dozen different sources contributed data to GHCN, only two sources are used for recent data. One of these is the U.S. Historical Climatology Network (USHCN; Easterling et al. 1996). USHCN data come from 1200 of the highest quality U.S. cooperative stations. However, data from USHCN are not available until 6–9 months after the observations were made. The second source of in situ data comes in near–real time. These are data transmitted over the Global Telecommunications System (GT) in CLIMAT code.

Climate data from approximately 1400 stations are exchanged internationally each month. A station's monthly mean temperature is calculated by the source station or country before being transmitted. While thousands more stations transmit synoptic messages over the GTS, monthly means derived from synoptic reports have serious data quality problems primarily because synoptic reports are seldom complete (e.g., Schneider 1992). Therefore, no data derived from synoptic sources are used in GHCN. The internationally agreed upon standard for transmission of CLIMAT messages calls for the data to be transmitted by the eighth day of the following month, although some data arrive later.

Not all CLIMAT data are incorporated into GHCN. In order to produce reliable quality control, robust measures of a station's long-term monthly mean and variance need to be produced. So CLIMAT stations without at least 10 yr of available data are not incorporated into GHCN.

The GHCN approach to quality control is to subject the data to a suite of tests (Peterson et al. 1998b): tests on the entire source dataset, tests looking at the time series as a whole, and tests on individual data points to make sure they are reasonable from a time series and a spatial perspective. If an individual data point is within 2.5 σ of its long-term monthly mean it passes the final quality control (QC) step. Data points between 2.5 and 5.0 σ from the mean undergo a spatial check to make sure neighboring stations also indicate that it was an exceptionally warm or cold month. If a neighbor agrees, the data point is considered good.

If the data from neighboring stations do not concur or if the datum was over 5.0 σ from the long-term mean, the datum is considered bad. However, every time new data points for that month are added, the potential for closer neighbors and improved spatial checking exists so the "bad" data points are reevaluated.

The vast majority of the transmitted CLIMAT messages have acceptable mean temperature data. GHCN's quality control removes the majority of the erroneous data caused by errors in digitization or transmission. However, a very few good data points without close enough neighbors to verify their extreme climate signal are probably removed from the dataset in this process and some erroneous but not extreme data points are retained, particularly in regions with high temporal variability. For example, when identical mean temperatures are transmitted for two consecutive months, it seems suspicious but possible. GHCN's QC does not flag such indications of possible problems until three data points in a row are identical.

Another problem with surface data is potential inhomogeneities in the station time series due to factors such as changes in location, new instrumentation, or changes in observing practices. GHCN mean temperature data undergo rigorous homogeneity testing (Peterson et al. 1998a). However, the GHCN adjustment methodology (Easterling and Peterson 1995; Peterson and Easterling 1994) requires 5 yr of data on either side of a potential discontinuity in order to make robust adjustments for the artificial change in the data record. Therefore, data from 1992 to the present can contain some inhomogeneities. However, GHCN minimizes the potential for inhomogeneities due to changes in methods used to calculate the mean monthly temperature from the daily or more frequent observations by preserving separate duplicate mean temperature time series for data from different sources if the duplicate time series are slightly different (Peterson and Vose 1997).

Under the auspices of the Global Climate Observing System (GCOS), effort is under way to encourage the exchange of data from the best climate stations around the world. Over the course of the next year or two, the GCOS surface network is ex-

pected to improve the quality and spatial distribution of stations reporting via CLIMAT (Peterson et al. 1997). The present distribution of CLIMAT stations leaves some areas, particularly in the Tropics, underrepresented. Figure 1 shows the locations of GHCN stations with at least 5 yr of data available during the period 1992–98. Unfortunately, not all of these stations report every month. A typical month has between 1000 and 1100 CLIMAT reports from stations with at least 5 yr of data between 1992 and 1998, with large portions of the Tropics exchanging little or no in situ climate observations.

4. Satellite-derived land surface air temperature data

A new method to derive land surface temperatures from SSM/I data was described in Basist et al. (1998). This method uses the relationship among the seven different microwave channels provided by the Defense Meteorological Satellite Program (DMSP) instrument to identify the land surface type and determine the percentage of a pixel that is liquid water each time the satellite flies overhead. Since water has an emissivity of 0.65 at 19 GHz, the impact surface wetness has on the observed brightness temperature can be determined. This adjustment is empirically calculated by using the relationship between in situ temperature measurements and satellite brightness temperature at the SSM/I frequencies.

Williams et al. (2000) expanded on this method using other surface and atmospheric conditions based on statistical relationships between in situ and satellite observations at the time of satellite overpass.
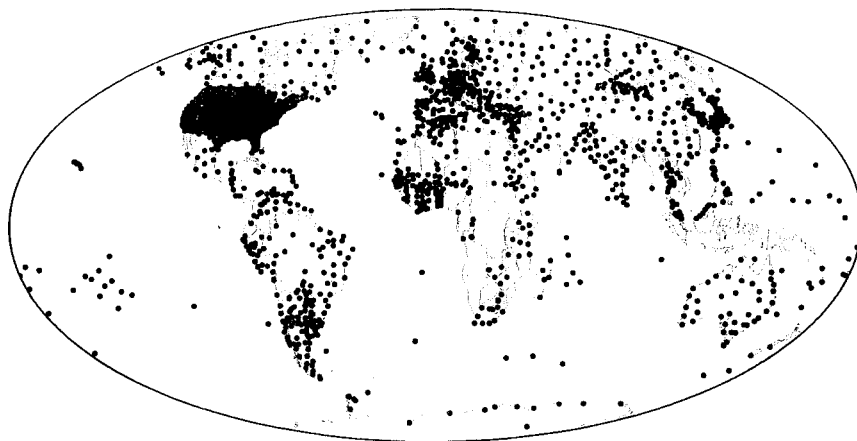

FIG. 1. Location of GHCN stations with 5 yr of data available during the 1992–98 period.

Intersatellite calibration and intrasatellite drift calculations were also addressed using comparisons with in situ observations. The results of these calibration procedures were independently validated with a different, higher-density network of in situ stations. This work was done using both instantaneous 1/3° pixel analyses and monthly 1° × 1° analyses.

A flowchart of our SSM/I processing steps is shown in Fig. 2. Starting with the 1/3° instantaneous pixel analysis described in Williams et al. (2000), 1° × 1° instantaneous temperatures were created. Morning and afternoon overpasses were processed separately. Over the area of a 1° × 1° grid box there can be considerable change in elevation and hence temperature. Therefore, a single pixel temperature may not be representative of the average grid box as a whole. An elevation-related temperature adjustment was created for each pixel so that its temperature could better represent the whole grid box for those times when data from all nine pixels were not available. The adjustment was based on the average difference between that pixel's temperature and the concurrent mean grid box temperature. Each pixel would have a different adjustment value for each month of the year

that was calculated from all the observations during all the years of data for that month.

To minimize the impact of extreme values in the above analyses, a biweight mean was used in the calculations (Lanzante 1996). If the data are normally distributed, biweight means are very similar to arithmetic means. But because biweight calculations use a nonlinear decrease in the weight given to data points the farther they are away from the median with values 5 σ (in this case) away from the median given zero weight, biweight analyses are minimally impacted by occasional odd values.

The first step in creating monthly values was to calculate 1° × 1° grid box temperatures for each satellite overpass. This value is simply the biweight mean of all adjusted pixel temperatures available at that time. Some orbits would have as few as one valid pixel temperature for use in the calculation of a grid box temperature, but most of the time all nine were available or none at all. Unfortunately, orbital gaps mean that some grid boxes have no data for one or more days in a row. This problem was addressed in two ways. The first way was to fill in the missing data for a grid box using a linear interpolation between observations before and after the missing days. Because of the autocorrelation of weather and climate, this interpolation improved monthly means. For example, if the fourth and sixth day of the month were cold, it is probable that the fifth was as well.

If the orbital gaps become too large, significant weather events can be missed entirely, which would decrease the accuracy of the analyses. Therefore, monthly means were not produced if there were seven or more days in a row missing, two cases of six days in a row missing, or three cases of five or more days in a row missing. These numbers were derived by balancing the need for accuracy with the benefit of having some data for the area present. Complete daily coverage would improve the results but is impossible to achieve. Monthly means were also not determined if there were five or more observations of snow. The SSM/I algorithm cannot derive surface temperature when there is snow on the ground. Treating snow observations as missing adds a small warm bias to the analyses of some grid box months, so these need to be limited.

For those months with adequate observations, arithmetic means of the daily values (real or linearly interpolated) were calculated. The next step was to turn the monthly value into an anomaly of the monthly period of record value for that grid box. At least 5 yr of data for that month are required for the base period
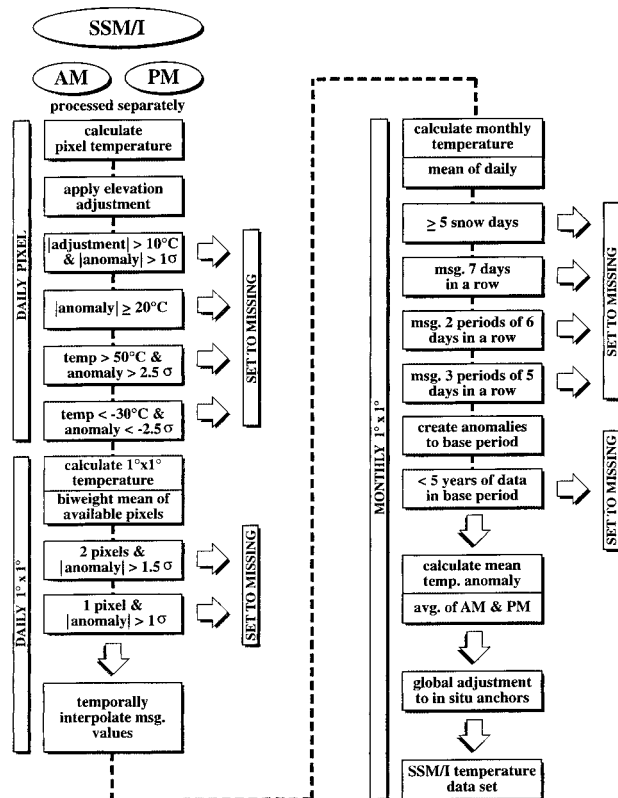

FIG. 2. A flowchart of the SSM/I-derived surface temperature processing steps.

from which the anomalies are calculated. Not all grid boxes have this. For example, for the period from 1992 to the present, a grid box may have only three Februarys without snow. In such cases, no February SSM/I data from this grid box could be used. Up through this stage, the SSM/I processing is still performed separately on morning and afternoon overpasses. The final step of making mean monthly temperatures is to calculate the mean of the morning anomaly and the evening overpass anomaly.

Additional quality control tests were applied at various stages in this process. For example, a mean for each $1/3°$ pixel was calculated from all years of a particular month and any data point greater than $20°C$ from the long-term mean was discarded. Extremely high (greater than $50°C$) or low (less than $-30°C$) values were also discarded if they were more than 2.5σ from the long-term pixel mean. Additionally, if the elevation-related adjustment for that pixel was larger than ±10 C, data from that pixel were only used if it was within 1σ of its mean. Furthermore, because the accuracy diminishes when we have fewer observations per grid box and some of the SSM/I-derived observations in the tail of the distributions have significant errors, as indicated in Williams et al. (2000), greater care must be taken when only one or two pixels in the grid box have data. Therefore, grid box values were not calculated if there was only one pixel and it was greater than 1σ from its long-term mean for that month of the year, or there were two pixels with a mean deviation in excess of 1.5σ.

Williams et al. (2000) indicated that the mean monthly $1° \times 1°$ SSM/I-derived temperature anomalies represented the climate of the area very well: they had a temporal correlation (r) with in situ anomalies greater than 0.8 and the differences from in situ anomalies have a variance of 0.76 with low kurtosis and skewness. Each step of the monthly derivation described here was designed to ensure that the analysis would be robust in diverse areas of the world and was evaluated to ensure that it preserved or improved the accuracy described in Williams et al. (2000). Using the dense in situ network in the eastern United States as verification, as per Williams et al. (2000), the more complex monthly averaging approach described above reduces the rms error to $0.71°C$. By comparison, a similar analysis of in situ stations indicates that this error is about twice that of a grid box value derived from a single in situ station and approximately the same as interpolating a single in situ station's data from $2°$ away.

5. Blending the data

Many possible approaches exist for combining different sources of data into one dataset. For example, Smith et al. (1998) produced a full grid of SST using the spatial and temporal covariance of the sea surface temperature field along with the available historical data. But every approach involves certain assumptions or trade-offs. Within Smith et al.'s (1998) approach, for example, is the assumption that the covariance pattern developed in the satellite era is an appropriate guide for interpolating data in earlier eras. One step in evaluating options to use for combining GHCN and SSM/I-derived observations, was comparison in the United States with the dense U.S. cooperative network serving as ground truth. These analyses indicated that interpolating an in situ station anomaly value from one degree away produced more accurate anomaly values than the SSM/I observations for that $1° \times 1°$ grid box. However, embedded within this evaluation was the assumption that all international data transmitted over the GTS would have the same high quality as the U.S. data quality controlled and archived at the National Climatic Data Center (NCDC).

Unfortunately, analysis of the global in situ data base indicates that this assumption simply is not valid. Individual satellite-derived and in situ values can have significant errors. Therefore, our approach to blending the data focused on minimizing the impact of significant though rare errors in each of the datasets rather than producing a dataset with a slightly more accurate mode. Toward this end, we (a) transformed the data into anomalies to the 1992–present base period so all interpolation or merging was done in anomaly space; (b) interpolated GHCN data out only a modest distance where the interpolated values are more reliable, covering a $5° \times 5°$ square centered on the station; (c) weighted all GHCN-derived values equally, that is, an anomaly value interpolated out $2°$ is given the same weight as a station in that $1° \times 1°$ grid box; and (d) gave the SSM/I anomaly value for a $1° \times 1°$ grid box the same weight as a single in situ station. This means that for land areas with many in situ observations, the final product primarily represents in situ anomalies. If there is only one station in the vicinity, the product reflects both the interpolated in situ and SSM/I-derived anomalies equally. Where no in situ data are present, the final product is purely SSM/I-derived anomalies (e.g., in much of the Tropics) or missing (e.g., snow-covered areas).

To ensure that changes in satellite drift or degradation of the SSM/I instrument do not impart a bias
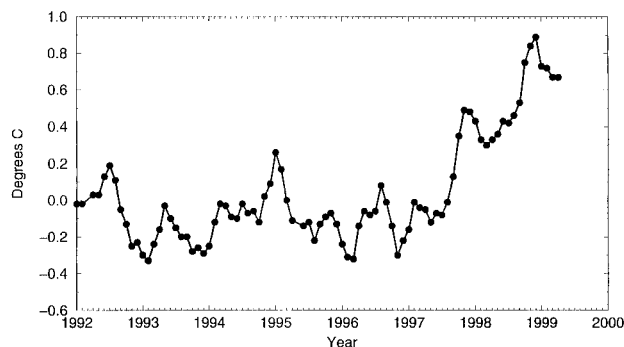
FIG. 3. Smoothed differences between collocated in situ and SSM/I anomalies. These values are applied to the SSM/I-derived anomalies to anchor the satellite analysis on the in situ values.

was calculated. The monthly anomaly used in this calculation was based on a mean of only those years that have both GHCN and collocated SSM/I temperatures. The mean difference for each calendar month was determined. Next, the monthly time series of these differences was smoothed with a three-month running average filter to allow more data points to contribute to the calculation of the adjustment. This smoothed difference value was then added to every $1° \times 1°$ SSM/I grid box anomaly value. As examination of Fig. 3 indicates, these adjustments are small during the time periods when the full period of record data for a satellite was available for calculating the intersatellite adjustment (Williams et al. 2000).

The SSM/I and in situ observations were gridded to the same $1° \times 1°$ grid used in the SST analysis. Using a land/sea mask and an ice value, SST data were limited to open ocean. The land data were supplied by the blended GHCN–SSM/I field. However, GHCN temperature anomalies were interpolated out two ad-
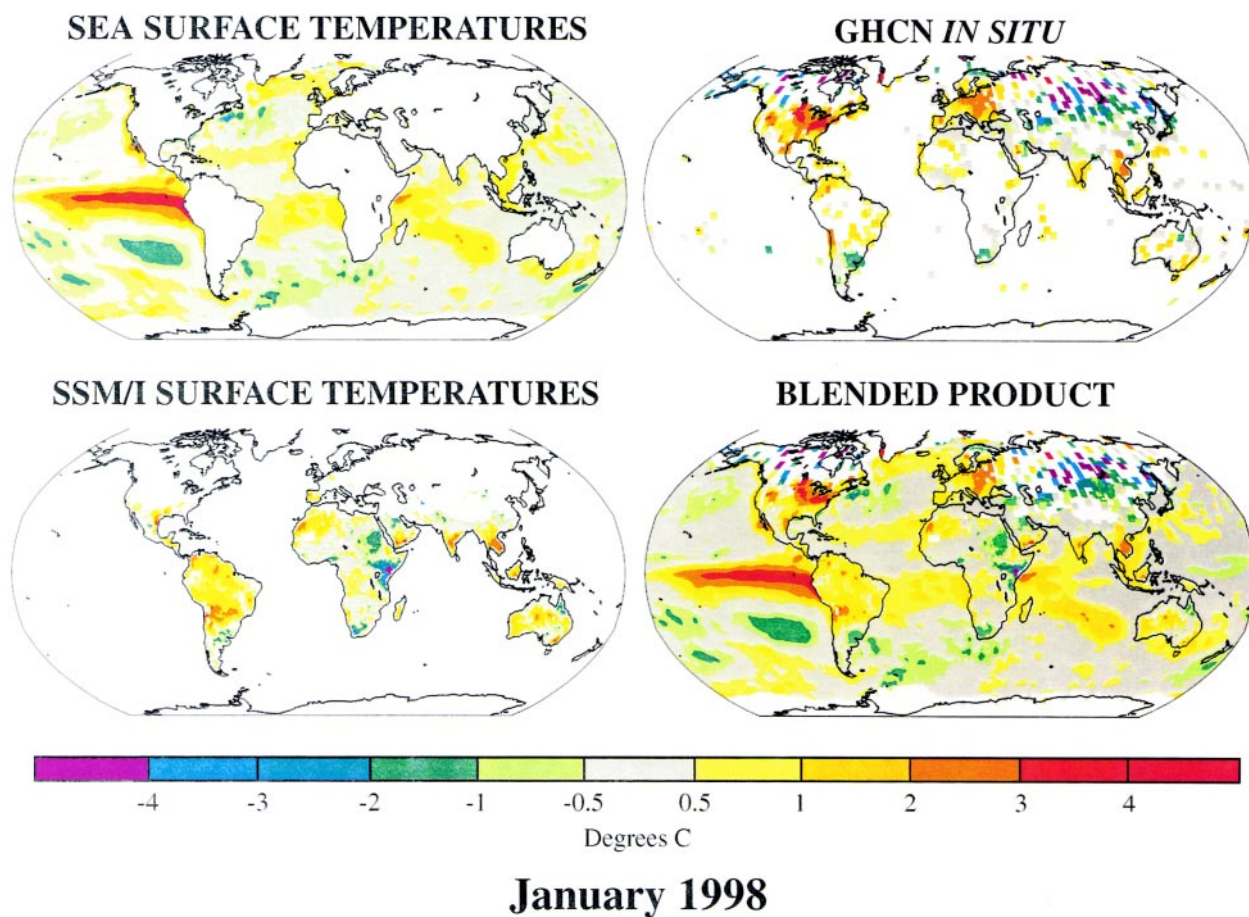
to the product, each month's SSM/I analysis was adjusted to anchor it on the in situ observations. The difference between every GHCN station monthly temperature anomaly and the SSM/I anomaly for the $1° \times 1°$ grid box containing the station, if available,

SEA SURFACE TEMPERATURES

GHCN IN SITU

SSM/I SURFACE TEMPERATURES

BLENDED PRODUCT

Degrees C

January 1998

FIG. 4. Gridded surface temperature anomaly fields, in °C, for Jan 1998 from (upper left) SSTs only, (upper right) GHCN in situ stations only, (lower left) SSM/I-derived surface temperature only, and (lower right) the full blended product.

ditional $1° \times 1°$ grid boxes in all directions that allow coastal stations to provide information over the ocean. In these cases, where there were no SST data available, that is, over the frozen Arctic Ocean, GHCN is used to provide anomalies for those grid boxes. However, if SST data were available, the values for those grid boxes come from SST data alone. Consequently, no compositing of the two data sources was done along coast lines. However, if a $1° \times 1°$ grid box does actually contain a GHCN station, such as a remote island, the anomaly used for this grid box comes from the land data and contains no input from the SST data source. Interestingly, the use of land data in remote islands is hard to detect because their anomalies are so close to the surrounding SST anomaly but along coastal zones there can be regions of strong contrast. Figures 4 and 5 show the input data and final product for two months, January 1998 and August 1998, respectively.

6. The near-global temperature dataset

The final $1° \times 1°$ product is not fully global. Snow- and ice-covered regions are limited to in situ observations. Note the excellent coverage in Figs. 4d and 5d in the in situ data-sparse Tropics. Clearly there is a spatial coherence to the structure of the monthly climate signal captured by this dataset. While it is not error free, it does clearly define the regions of significant climate anomalies and is therefore very useful for monitoring the climate in regions that were previously data sparse. Because it provides information in data-sparse areas, quantifying the accuracy of the blended dataset throughout the world is difficult. However, we continue to assess the product's accuracy whenever supplemental data for a region becomes available.

The blended global surface temperature anomaly dataset version 1A is available from the NCDC/ NESDIS/NOAA through anonymous ftp (http:// www.ncdc.noaa.gov/ol/climate/research/blended/ blended.html). This site also contains links to monthly
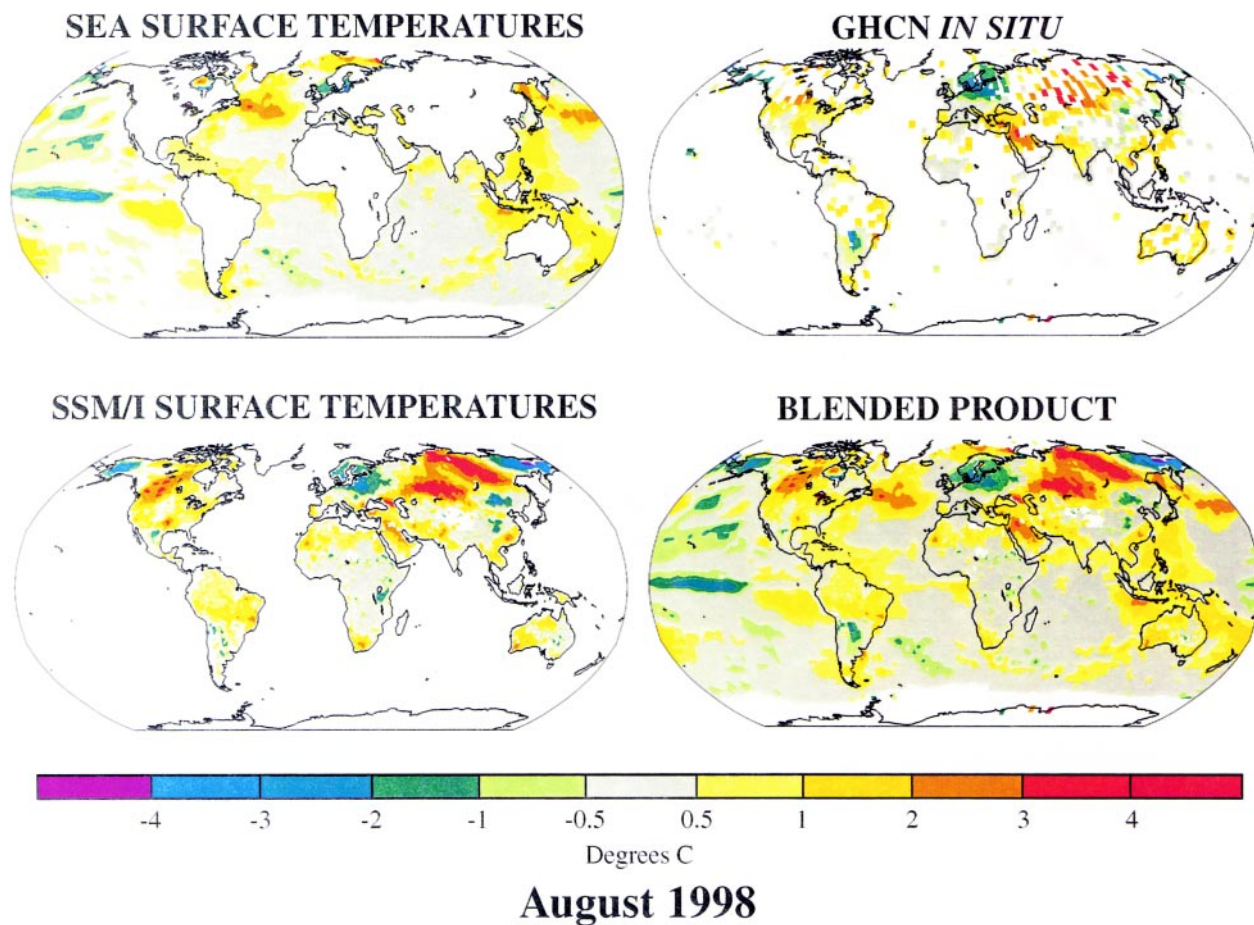

Fig. 5. The same as Fig. 4 but for Aug 1998.

images of the anomaly fields. The data start in January 1992 and are updated about 10 days after the end of the month. Two months during this period do not have adequate SSM/I data to create any SSM/I-derived monthly temperature anomalies. One of the planned improvements will be reprocessing the orbital data archived at NCDC. This will help fill in some missing data points and regrid the SSM/I data in a more rigorous fashion, which should improve the accuracy of the final product. Data from SSM/I satellites with different overpass times will also be incorporated. Other ways to improve the SSM/I temperature algorithm and blending of in situ and SSM/I-derived temperatures will continue to be investigated.

The present product is clearly better than any of the sources alone. For example, insights into the climate can be obtained by seeing the transition between SST and continental air temperatures, which in some instances is very smooth and in other cases has abrupt changes. The SSM/I-derived temperatures provide dramatically improved coverage over in situ data in some climatologically important areas and at the same time the SSM/I temperatures are improved by anchoring the monthly anomalies on in situ observations. Blended together, the three sources of data provide near-global coverage.

References

Basist, A., N. C. Grody, T. C. Peterson, and C. N. Williams, 1998: Using the Special Sensor Microwave Imager to monitor land surface temperatures, wetness, and snow cover. *J. Appl. Meteor.,* **37,** 888–911.

Easterling, D. R., and T. C. Peterson, 1995: A new method for detecting and adjusting for undocumented discontinuities in climatological time series. *Int. J. Climatol.,* **15,** 369–377.

——, T. R. Karl, E. H. Mason, P. Y. Hughes, and D. P. Bowman, 1996: United States Historical Climatology Network (U.S. HCN) monthly temperature and precipitation data. ORNL/CDIAC-87, NDP-019/R3, Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, Oak Ridge, TN, 280 pp.

Lanzante, J. R., 1996: Resistant, robust and nonparametric techniques for the analysis of climate data: Theory and examples, including applications to historical radiosonde station data. *Int. J. Climatol.,* **16,** 1197–1226.

Peterson, T. C., and D. R. Easterling, 1994: Creation of homogeneous composite climatological reference series. *Int. J. Climatol.,* **14,** 671–679.

——, and R. S. Vose, 1997: An overview of the Global Historical Climatology Network temperature data base. *Bull. Amer. Meteor. Soc.,* **78,** 2837–2849.

——, H. Daan, and P. Jones, 1997: Initial selection of a GCOS surface network. *Bull. Amer. Meteor. Soc.,* **78,** 2145–2152.

——, 1998a: Homogeneity adjustments of in situ atmospheric climate data: A review. *Int. J. Climatol.,* **18,** 1493–1517.

——, R. S. Vose, R. Schmoyer, and V. Razuvaëv, 1998b: GHCN quality control of monthly temperature data. *Int. J. Climatol.,* **18,** 1169–1179.

Reynolds, R. W., and D. C. Marsico, 1993: An improved real time global SST analysis. *J. Climate,* **6,** 114–119.

——, and T. M. Smith, 1994: Improved global sea surface temperature analyses using optimum interpolation. *J. Climate,* **7,** 929–948.

Schneider, U., 1992: The GPCC quality-control system for gauge-measured precipitation data. Report of a GEWEX Workshop, Koblenz, Germany, WMO/TD-No. 558. [Available from World Meteorological Organization, 7 bis Avenue de la Paix, CP 2300-1211 Geneva 2, Switzerland.]

Smith, T. M., R. E. Livezey, and S. S. Shen, 1998; An improved method for analyzing sparse and irregularly distributed SST data on a regular grid: The tropical Pacific Ocean. *J. Climate,* **11,** 1717–1729.

Williams, C., A. Basist, T. C. Peterson, and N. Grody, 2000: Calibration and validation of land surface temperature anomalies derived from the SSM/I. *Bull. Amer. Meteor. Soc.,* **81,** 2141–2156.